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The Relationship Between System User's Tasks and Business Intelligence (BI) Success in a Public Healthcare Setting

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Abstract: In this study, the relationship between task characteristics and business intelligence (BI) success is empirically tested on a business intelligence system in an e-Government context in Denmark. The purpose of the study is to investigate which tasks contribute to BI success. A total of 1.351 end users replied to the questionnaire, and the response rate was 32%. In this study, task compatibility and task difficulty have a substantial relationship with user satisfaction. The relationship between task significance and use was also substantial, as well as the relationship between user satisfaction and individual impact. The model was a good fit, having a relatively high determination coefficient and predictive relevance. Therefore, the study determined that tasks are important factors contributing to BI success.

Keywords: task characteristics, business intelligence success, public sector, quantitative research

1. Introduction

In recent decades, there has been an increasing focus on using information technology in the public sector to provide transparent and efficient government services (Chourabi, Mellouli, and Bouslama, 2009). e-Government can be defined as the government's use of information technology, particularly web applications, to enhance the access and delivery of government information to employees, business partners, citizens, politicians and other stakeholders (Torres, Pina, and Royo, 2005). There are several differences between public and private organisations regarding management, fundamental objectives and governance (Azari and Pick, 2009). Furthermore, Governments are under pressure to reduce costs as well as deliver high-quality services (Fernandes, Alencar, Schmitz, and Correa, 2014). More complexity is required in the public sector's IT infrastructure because of the broad responsibilities supported by technology. These responsibilities include the health sector, social services, public transport, labour market policy, child care, primary school, and environmental policies (Kommunernes Landsforening, 2017). Denmark has 4,200 different IT systems for federal IT-support workflows (Finansministeriet, 2017). In addition, other systems exist at the regional and municipal levels.

In the public sector, attention has been paid to the potential value of data. Every day, large amounts of data are generated through daily operations, such as pension payments, tax payments, billing and healthcare reporting (Cavanillas, Curry, and Wahlster, 2016). An answer to management challenges in the public sector is to use data analysis to support decision-making. Wixom and Watson (2010) have defined business intelligence (BI) as: ' … an umbrella term that is commonly used to describe the technologies, applications, and processes for gathering, storing, accessing, and analysing data to help users make better decisions'. In general, many organisations implement BI due to its potential impact on business performance (Hawking and Sellitto, 2010; Watson and Wixom, 2007). Therefore, BI success is vital to the organisations investing in technology.

Democratic governments are some of the largest users of IT worldwide. Due to the differences between private- and public-sector tasks and the complexity of their IT requirements, the concepts, methods and techniques developed in the private sector may not necessarily be transferable to the public sector. Most research in this area focuses on private-sector organisations (Rosacker and Olson, 2008), including critical success factors for BI success; there are few studies of BI in a public-sector setting (Gaardboe and Svarre, 2017). Technological developments within BI have meant that more employees have access to these tools, such as through a browser. According to Svarre and Lykke (2013), the development of technologies, organisations and governmental processes are expected to change the tasks of government employees. From the literature, we know that there is a relationship between different task characteristics and information systems' (IS) success (Petter, DeLone, and McLean, 2013). However, only four studies have, to our knowledge, focused on the relationship between task compatibility and BI success (Arnott, 2008; Khojasteh, Ansari, and Abadi, 2013; Olszak and Ziemba, 2012; Ravasan and Savoji, 2014). Other task characteristics and BI success have not yet been investigated (Gaardboe and Svarre, 2017). Therefore, this study sought to test the effects of

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task characteristics on BI success empirically (e.g., the three constructs 'use,' 'user satisfaction' and 'individual impact') in a government setting. This article will contribute to the subfield of BI success and especially, BI success in an e-Government.

The paper is structured as follows; in the following section, literature related to BI success in an e-Government is presented, followed by a research model testing the influence of task characteristics on BI success. The next section presents the research methods applied in the study, including a survey questionnaire, followed by an assessment of partial least square (PLS). The subsequent section presents findings on the relationship between several task characteristics and BI success, followed by a discussion of the findings. The paper concludes with concluding remarks, limitations and suggestions for further research.

2. Research model

2.1 Related research

In the field of BI success and e-Government, only a few studies have been performed. Tona, Carlsson and Eom (2012) studied BI success at a Swedish police station. Their studies showed that system quality contributes to success regarding use and user satisfaction and that there is a positive relationship between information quality and user satisfaction. Moreover, both user satisfaction and use are positively associated with individual impact. Nasab, Selamat and Masrom (2015) studied business intelligence success in Malaysia's public sector. They concluded that scalable and flexible BI, continuous management support, resource allocation, BI team skills, organisational culture and coordination between IT and business units were the most important critical success factors. However, none of the studies focused on the importance of the tasks from the perspective of success with business intelligence.

Gaardboe and Svarre (2017) performed a literature review to identify the critical success factors for achieving BI success. In the study, 33 different constructs were identified. The research gap was identified to specifically address the importance of the tasks for success with BI. Petter, DeLone and McLean (2013) have identified six different task characteristics that could influence IS success, including task compatibility, task difficulty, task interdependence, task variability, task significance and task specificity. Much of the recent literature has not focused on the role of task characteristics as critical success factors in BI success (Gaardboe and Svarre, 2017). However, it is recognised within the information system literature that task characteristics can be a factor (Petter et al., 2013). Although, tasks are a known construct in contingency literature within information systems (Weill and Olson, 1989). According to Petter, DeLone and McLean (2013) task compatibility and task difficulty are moderate determinants of IS success. The other assignment characteristics have been explored very little in IS success literature. The task of the user is important because it affects the value of the technology (Trkman, McCormack, de Oliveira, and Ladeira, 2010).

2.2 Task characteristics

A task can be defined as a particular item of work. When the user is performing a task, it has a recognisable beginning and end. The task also has a practical result and, under normal circumstances, a meaningful purpose (Byström, 2002). Byström (2007) has identified three different research foci; focus on tasks within the system perspective; focus on tasks within the individual (user) perspective and focus on tasks within the socio-cultural perspective. This article focuses on tasks from a system perspective, specifically, the BI system and function and its many different kinds of users (Byström, 2007). Freund, Clarke and Toms (2006) have reported that task classification is more likely to be operationally than theoretically oriented. This article adopts classifications from Petter, DeLone and McLean (2013), except for task variability. The construct task variability has been defined as the degree of consistency between the task and the user. Since the focus of this paper is on tasks related to the BI system, the characteristic of task variability was left out. The concept of task characteristics provides a framework for analysing the relationship between the BI system users' task and BI success. The five reminding task characteristics are task compatibility, task significance, task interdependence, task difficulty and task specificity. In the section below, the task characteristics and the relationship to BI success are presented.

Task compatibility is the fit between the task, the user who performs it and the BI system that is utilised (Petter et al., 2013). According to Goodhue (1988), if there is a correspondence between the employee's task and the functionality of the system, an impact on performance will occur. The rationale behind this is that if the task compatibility is high, the user will use the system and the user satisfaction will be high and vice versa.

Task significance is the importance of the task and the impact of task abandonment on the individual process or the organisation (Petter et al., 2013). In the case of information systems, it is how important the task is when it is resolved with business intelligence. Within research on information systems, it is the relationship between use and impact that have been investigated (Lim, Pan, and Tan, 2005; Venkatesh and Davis, 2000).

Task interdependence is the degree to which the task performed in the IS is dependent on other tasks or processes for completion (Petter et al., 2013). Task interdependence increases when a task cannot be completed due to a dependence on others. According to Straus and McGrath (1994), an increased level of task interdependence requires more information exchange to clarify the task assignment, project requirements and progress. Task interdependence is related to the effectiveness of a group (Vandenbosch and Ginzberg, 1997). In this article, it is a measure of whatever tasks the user cannot complete by him or herself.

Task difficulty is the degree to which the task supporting BI is a challenge for the user (Petter et al., 2013). In IS research, task difficulty has an inverse relationship to IS success. Therefore, easy tasks are related to successful IS. The primary dependent variables have been user satisfaction and individual impact (Petter et al., 2013).

Task specificity is the level of clarity of the task supported by the IS (Petter et al., 2013). Within IS research, there have been mixed results regarding how task specificity influences IS success. Kim, Kim, Aiken and Park (2006) found a relationship between task specificity and individual impact. However, two other studies have had mixed results (Petter et al., 2013).

2.3 Business Intelligence Success

In this article, BI success is defined as a positive impact on one or more of the three constructs; user satisfaction, use and individual impact. The three constructs are well known in the field of IS research (DeLone and McLean, 1992, 2003). Moreover, the three constructs are the dependent variables most used as a measure of success (Petter, DeLone, and McLean, 2008; Petter et al., 2013).

Bailey and Pearson (1983, p. 531) define user satisfaction as, ”the applicable definition of satisfaction is the sum of the user's weighted reactions to a set of factors.” Several studies have been conducted on various IS systems to determine how satisfied the user is with the system. Often, a system is necessary for end users to perform a job function. Therefore, user satisfaction must be measured by the specific system (Hsieh, Rai, Petter, and Zhang, 2012). In this study, user satisfaction is measured as the overall satisfaction. As described before, the different task characteristics are related to user satisfaction. However, user satisfaction is also related to the two other BI success factors, including use and individual impact (DeLone and McLean, 1992, 2003).

Another BI success construct is use. Use is the way and extent to which users use the system’s capabilities (Petter et al., 2013). Thus, Seddon (1997) has defined three ways in which use can be understood. First, use can be understood as a variable that is a proxy impact from the system. Secondly, use may be an expression of the user’s intention to use the system. Third, use can be understood as an event in a process that leads to impact. In this study, use is understood as the third understanding. In the literature, a relationship exists between use and user satisfaction and between use and individual impact (Petter et al., 2008).

The last BI success construct is individual impact, which can be defined as “an indication that an information system has given the user a better understanding of the decision context, has improved his or her decision-making productivity, has produced a change in user activity, or has changed the decision maker’s perception of the importance or usefulness of the information system” (DeLone and McLean, 1992, p. 69). According to DeLone and McLean, use and user satisfaction have a positive (or negative) impact from the user’s perspective (DeLone and McLean, 2003).

2.4 Hypothesis

This article focuses on the relationship between task characteristics and business intelligence success from a system user perspective. Our model is shown in the figure below.

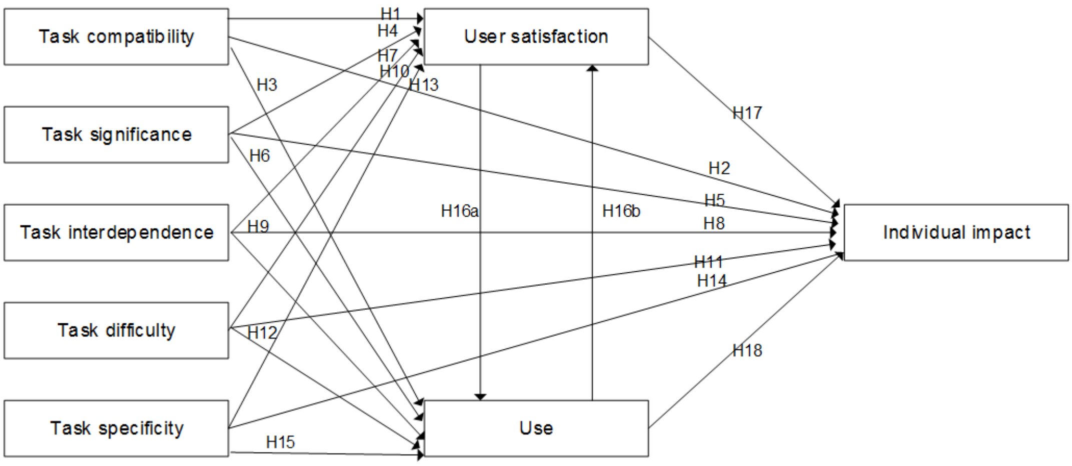

Figure 1: Research model, the relationship between task characteristics and BI success

3. Method

3.1 The context of the Study

A survey was sent out to a one of the five regions in Denmark. A region has the administrative and political responsibility for health, the labour market and public transport in a geographically defined area and are financed by the state and municipalities. The council is directly elected and has a political responsibility for these sectors. The region included in this study has more than one million inhabitants, a budget of over 3 million euro and about 25,000 employees. The employees operate in an environment that is characterised by politically motivated priorities. At hospitals, employees experience pressure that they should be efficient, comply with the budget, and sometimes, the resources are reallocated to other diseases. Moreover, the regions have a complex portfolio of different IT systems and derive various data and data types. Therefore, BI is used to provide information to make better decisions in the public healthcare sector.

All health and administrative staff working with public healthcare in the region have access to the BI. The region uses Tableau, as employees have access through a browser. System users can view and analyse data. Users use data for reporting, ad hoc analyses, and follow up on treatments. They use both economic and quality indicators. System usage is mandated as part of the information and can only be accessed in BI and not in other systems.

3.2 Data collection and analysis

Data was collected using a quantitative approach. A questionnaire (Appendix A) was created in an online survey program, based on questions that had been used, tested and validated in previous studies (Batenburg and Van den Broek, 2008; Daft and Macintosh, 1981; DeLone and McLean, 1992; Lee, Strong, Kahn, and Wang, 2002; Lewis, 1995; Morgeson and Humphrey, 2006; Wang and Liao, 2008). The items were measured using a 5-point Likert scale. All system users of BI employed in the region were asked to participate in the study. Of approximately 4,232 potential users, 1,351 questionnaires were obtained. Of the 1,351 respondents, only 746 were users of the BI system. In this study, we were interested in the users' perceptions. This paper is part of a larger study, and a part of the dataset has been used to assess DeLone and McLeans' (1992) IS success model' (Gaardboe, Sandalgaard, and Nyvang, 2017).

The model in Figure 1 is tested with Partial Least Squares Structural Equation Modelling (PLS). PLS models the structural and have measurement paths (Hair, Hult, Ringle, and Sarstedt, 2017). The model is tested using SmartPLS 3.2.7. Hence, there exists a mutual influence between user satisfaction and use. Two models are tested. Model 1 includes user satisfaction as a predictor of use and Model 2 includes use as a predictor of user satisfaction.

3.3 Measurement Model Estimation

Partial least squares were used for testing the model for the measurement and structural paths. The model in Figure 1 was tested by using a SmartPLS 3.2.7. Before testing the relationships in the model, the first step was to evaluate the measurement model. The model consisted of both reflective and formative measures, where there were different procedures for measuring the validity and reliability (Hair et al., 2017). Therefore, first, the reflection measures and then the formative measures were reviewed. The four reflective measures were individual impact, task compatibility, task significance and user satisfaction. The formative measures included task difficulty, task interdependence and task specificity. Use is a single item construct, and therefore, it was not evaluated.

3.3.1 Testing the Validity and Reliability of Reflective Constructs

First, the internal consistency was assessed by calculating Cronbach's alpha and composite reliability (Hair et al., 2017). Nunnally and Burnstein (1994) recommended a threshold value of 0.7. Based on the values in Table 1, we concluded that the requirements for internal consistency were met.

Table 1: Cronbach's Alpha, Composite Reliability and Average Variance Extracted (AVE)

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Individual Impact	0.844	0.906	0.762
Task Compatibility	0.817	0.879	0.647
Task Significance	0.776	0.845	0.531
User Satisfaction	0.882	0.927	0.809

Afterwards, the convergent validity was assessed based on indicator reliability and average variance extracted (AVE) (Hair et al., 2017). According to Fornell and Larcker (1981), the variance of the construct is larger than the error if the values are above 0.5.

The size of the outer loading assessed the indicator reliability. All reflective measured constructs were significant and had a p-value below 0.001. Table 2 summarises the results of the assessment of the different measures of the outer loading and HTMT.

Table 2: Outer Loadings Value, P-Values and HTMT

Construct	Instruments	Outer Loading	P-Values	HTMT interval does not include 1
Individual Impact	IndImp01 <- Individual Impact	0.911	0.000	Yes
	IndImp02 <- Individual Impact	0.877	0.000	
	IndImp03 <- Individual Impact	0.825	0.000	
Task Compatibility	TaskCom01 <- Task Compatibility	0.778	0.000	Yes
	TaskCom02 <- Task Compatibility	0.788	0.000	
	TaskCom03 <- Task Compatibility	0.760	0.000	
	TaskCom04 <- Task Compatibility	0.886	0.000	
Task Significance	TaskSig01 <- Task Significance	0.820	0.000	Yes
	TaskSig02 <- Task Significance	0.752	0.000	
	TaskSig03 <- Task Significance	0.786	0.000	
	TaskSig04 <- Task Significance	0.782	0.000	
	TaskSig05 <- Task Significance	0.434	0.000	
User Satisfaction	UserSat01 <- User Satisfaction	0.853	0.000	Yes
	UserSat02 <- User Satisfaction	0.907	0.000	
	UserSat03 <- User Satisfaction	0.927	0.000	

The indicator reliability was assessed by the size of the outer loading. All reflective measured constructs were significant and had a p-value below 0.001. The Heterotrait-Monotrait Ratio (HTMT) was calculated to examine discriminant validity. According to Hair et al. (2017), this is a better measure because the typically used cross-loadings do not allow for the reliable detection of discriminant validity issues. The HTMT interval was calculated and did not include the number 1. Therefore, the discriminant validity of the constructs was acceptable. All the evaluation criteria were met, which provided support for all the measures' reliability and validity.

3.3.2 *Testing the Validity and Reliability of Formative Constructs*

To assess the formative indicators, the guidelines by Hair et al. (2017) were used. First, the collinearity of indicators was examined. Secondly, the outer weight and outer loading are assessed.

The threshold value for VIF is between 0.2 and 5. All indicators in Table 3 are within this range. Afterwards, each indicator was assessed according to outer weight and outer loading. First, outer weight is significant if the item is retained in the model. Therefore, TaskDiff01 is retained in the model. If the outer weight is insignificant, but the outer loadings are above 0.5, then the item is also retained in the model. Thus, TaskInt01 and TaskSpe02 are retained in the model. The remaining items are left out of the model.

Table 3: Assessment of VIF, Outer Weight and Outer Loadings

Item	VIF	Outer Weight	P-Values	Outer Loadings	P-Values	Evaluation
TaskDif01	1.019	0.999	0.000	0.988	0.000	Retain
TaskDif02	1.064	-0.088	0.282	0.020	0.828	Remove
TaskDif03	1.046	-0.107	0.192	-0.135	0.128	Remove
TaskInt01	1.038	0.776	0.103	0.826	0.099	Retain
TaskInt02	1.076	0.134	0.468	0.157	0.342	Remove
TaskInt03I	1.046	-0.577	0.213	-0.586	0.209	Remove
TaskSpe01I	1.037	-0.315	0.333	-0.418	0.277	Remove
TaskSpe02	1.012	0.910	0.117	0.932	0.118	Retain
TaskSpe03	1.031	-0.138	0.527	-0.148	0.507	Remove

4. Results

Based on the structural analyses, the findings of this study regarding the hypotheses are shown in Table 4.

Table 4: Results of the hypothesis. P values below 0,05 is significant

		Model 1		Model 2		Conclusion
Hypothesis		**Coef.**	**P Values**	**Coef.**	**P Values**	
H1	Task Compatibility -> User Satisfaction	0,464	0,000	0,461	0,000	Significant
H2	Task Compatibility -> Individual Impact	0,054	0,112	0,054	0,118	Insignificant
H3	Task Compatibility -> Use	0,005	0,916	0,046	0,238	Insignificant
H4	Task Significance -> User Satisfaction	0,072	0,048	0,053	0,168	Insignificant
H5	Task Significance -> Individual Impact	0,074	0,020	0,074	0,019	Significant
H6	Task Significance -> Use	0,274	0,000	0,281	0,000	Significant
H7	Task Interdependence -> User Satisfaction	-0,007	0,853	-0,011	0,760	Insignificant
H8	Task Interdependence -> Individual Impact	0,015	0,615	0,015	0,612	Insignificant
H9	Task Interdependence -> Use	0,071	0,055	0,071	0,058	Significant(Model 1) / Insignificant (Model 2)
H10	Task Difficulty -> User Satisfaction	0,191	0,000	0,189	0,000	Significant
H11	Task Difficulty -> Individual Impact	0,025	0,429	0,025	0,432	Insignificant
H12	Task Difficulty -> Use	0,009	0,817	0,026	0,515	Insignificant
H13	Task Specificy -> User Satisfaction	0,033	0,370	0,03	0,396	Insignificant
H14	Task Specificy -> Individual Impact	-0,022	0,378	-0,022	0,372	Insignificant
H15	Task Specificy -> Use	0,032	0,351	0,035	0,309	Insignificant
H16a	User Satisfaction -> Use	0,089	0,024			Significant
H16b	Use -> User Satisfaction			0,063	0,028	Significant
H17	User Satisfaction -> Individual Impact	0,695	0,000	0,695	0,000	Significant
H18	Use -> Individual Impact	-0,012	0,581	-0,012	0,594	Insignificant

In this study, the relationships between task characteristics and success constructs were analysed, as shown in Figure 1. The PLS results are shown in Table 4. The two constructs, task compatibility (H1) and task difficulty, are both positive and significantly related to user satisfaction (H10 and $p<0,001$). System users who find that there is a fit between their tasks have a higher user satisfaction. Furthermore, if the users find the task and solve with BI difficulty, they are also more likely to be satisfied. Model 1 is the relationship between task significance and user satisfaction, which is positive and significant (H4 and $p<0,05$); however, in Model 2, the result is insignificant (H4). The relationship between task significance and the two other BI success constructs is the same in both Model 1 and Model 2. Task significance is positively and significantly related to both use (H6 and $p<0,001$) and individual impact (H5 and $p<0,05$). The more important the user experiences the task they perform with BI, the higher the user satisfaction and individual impact. The mutual dependence between use and user satisfaction is found in both directions to be positive and significant (H16a, H16b and $p<0.05$). If the user uses BI more, then it will positively affect the user's satisfaction. In addition, those users who have a higher user satisfaction will use BI more. Between the two constructs, user satisfaction and individual impact, there is a positive and significant relationship (H17 and $p<0.001$). The higher the user satisfaction, the more the user experiences the individual impact of BI. The other hypotheses are insignificant.

The coefficient of determination (R^2) is the most common measure to evaluate the model's predictive power. In the table below, $R^2_{adj.}$ are reported for Model 1 and 2.

Table 5: The adjusted coefficient of determination for use, user satisfaction and individual impact

	Model 1	**Model 2**
	R Square Adjusted	**R Square Adjusted**
Individual Impact	0,566	0,566
Use	0,121	0,117
User Satisfaction	0,375	0,378

The results in Table 5 show that the variance of individual impact is explained 56,6% in both models, while the variance of user satisfaction is explained 37,5% in Model 1 and 37,8% in Model 2. Finally, use is explained 12,1% in Model 1 and 11,7% in Model 2. Additionally, to $R^2_{adj.}$ the effect size (f^2) is evaluated. The purpose is to test whenever an exogenous construct has a substantive impact on the endogenous construct (Hair et al., 2017). According to Cohen (1988), the f^2 values of 0,02, 0,15 and 0,35 is represented as small, medium and large effects. In both models, task compatibility has a medium effect on user satisfaction (f^2=0,248/0,246). Task difficulty has a low effect on user satisfaction (f^2=0,042/0,042), while task significance has a low effect on use (f^2=0,062/0,065). Finally, user satisfaction has a large effect on individual impact in both models (f^2=0,693/0,693).

In PLS, the standardized root mean square residual can be used to measure a fit (Hair et al., 2017). The SRMR value was 0.057 in both models. According to Hair et al. (2017), a value below 0.08 indicates the model has a good fit. Finally, the predictive relevance is tested for the model (Q^2). According to Hair et al. (2017, p. 202) is this measure ”… an indicator of the model's out-of-sample predictive power or predictive relevance.” The value of Q^2 is above the threshold value 0 for use, user satisfaction and individual impact. Therefore, the two tested models have predictive relevance.

5. Discussion and conclusion

The present study was designed to determine the relationship and effect between system users different task characteristics and BI success, which were empirically examined in a public healthcare setting. The extensive survey provided us with information about the relationships among the different constructs in Figure 1. The contribution from the paper goes beyond earlier published research. Firstly, because the study includes five task characteristics and earlier studies about BI success only included task compatibility (Gaardboe and Svarre, 2017). Secondly, the relationships between task characteristics and BI are tested for both significance and effect size (f^2), which has not been reported and analysed in other studies regarding task characteritics and BI success. When a relationship is both significant and there is an effect, it is called a substantive relation (Hair et al., 2017). In this study, four relationships are substantial.

The relationship between task compatibility and user satisfaction was positive and substantial. High task compatibility leads to higher user satisfaction, a result similar to those found in several studies in the IS field

(Jarupathirun and Zahedi, 2007; Petter et al., 2013). Relating this fact to the context in which this system was evaluated, we concluded that the employees of the region were more satisfied when the BI system fit into the tasks they completed. Specifically, having data that was relevant for their task was a major factor for task compatibility. Another substantial relation is between task difficulty and user satisfaction. When the user perceived a task as difficult, then they were more likely to rate the user satisfaction higher. This relationship has also been supported by other studies (Gelderman, 2002; Yoon, Guimaraes, and O'Neal, 1995). Task significance is also positively and substantially related to use. This result was also supported in a study by Lim et al. (2005). Finally, there is a positive and substantial relationship between user satisfaction and individual impact. According to Petter, DeLone and McLean (Petter et al., 2008), there is strong support for the relationship. The relationship mentioned before has been confirmed in this study.

In this study, four relationships are positive and significant; task significance and individual impact, task significance and user satisfaction (Model 1), user satisfaction and use, use and user satisfaction. Common to all relationships is that they are positive and significant, but the relationship does not affect the coefficient of determination (R^2) if the relationship is omitted by the model (Hair et al., 2017). On this basis, it can be concluded that the substantive relationships are more important than the significant relationships. Surprisingly, the relationship between use and individual impact was insignificant, while the path between use and individual impact is insignificant. Therefore, a change in use will not lead to a change in individual impact. Other researchers had the same finding (McGill, Hobbs, and Kolbas, 2003). An explanation may be that the use of the system is mandatory. According to Iivari (2005), the binding nature of an IS can inflate the significance of use. Therefore, more use will likely lead to individual impact, because it only makes sense to use the system when it fits the task.

In conclusion, this research is a comprehensive study of the various task characteristics. Therefore, a methodological contribution is also a questionnaire, where the different task characteristics are operationalised. This study has shown that the questionnaire can be used to characterise the tasks, as different kinds of BI users are solving with BI. The practical implications of the study are that when organizations know the task of characterization for BI success, they can be aware of the factors when implementing and operating the system. This may be useful to know when developing reports in BI. Conclusion In this study, the relationship between task characteristics and BI success were investigated. Within IS research, and especially BI and e-Government research, it has been an overlooked relationship. In this study, task compatibility and task difficulty has a substantial relationship with user satisfaction. The relationship between task significance and use was also substantial, as well as the relationship between user satisfaction and individual impact.

Two task characteristics that were not supported was not related to BI success; task specificity and task interdependence. Some researchers have suggested that user satisfaction could be a general measure of success. This study shows that the different task characteristics are related to various measures of success. Therefore, BI success should not only be measured, but measured using several values to understand the role of the various task characteristics. Thus, the model has a good fit and a relatively high degree of explanation.

The findings in this study are subject to at least two limitations. Firstly, this study has been conducted in a public healthcare setting with a specific BI system. Secondly, some constructs are single-items, whereby there may be some shades that have not been examined in the study.

Further research could focus on the relationship between all task characteristics and IS success. To investigate which task characteristics do contribute to success, future research can also address the relationship between task characteristics and BI success with different BI systems in different organisational settings.

References

Arnott, D., 2008. Success factors for data warehouse and business intelligence systems. In *ACIS 2008 Proceedings - 19th Australasian Conference on Information Systems* (pp. 55–65). Christchurch.

Azari, R., and Pick, J. B., 2009. Understanding global digital inequality: The impact of government, investment in business and technology, and socioeconomic factors on technology utilization. In *System Sciences, 2009. HICSS'09. 42nd Hawaii International Conference on* (pp. 1–10). IEEE. Retrieved from http://ieeexplore.ieee.org/abstract/document/4755485/

Bailey, J. E., and Pearson, S. W., 1983. Development of a tool for measuring and analyzing computer user satisfaction. *Management Science*, *29*(5), 530–545.
Batenburg, R., and Van den Broek, E., 2008. Pharmacy information systems: the experience and user satisfaction within a chain of Dutch pharmacies. *International Journal of Electronic Healthcare*, *4*(2), 119–131.
Byström, K., 2002. Information and information sources in tasks of varying complexity. *Journal of the American Society for Information Science and Technology*, *53*(7), 581–591. https://doi.org/10.1002/asi.10064
Byström, K., 2007. Approaches to "task" in contemporary information studies. In *Proceedings of the Sixth International Conference on Conceptions of Library and Information Science—"Featuring the Future."*
Cavanillas, J. M., Curry, E., and Wahlster, W., 2016. The Big Data Value Opportunity. In J. M. Cavanillas, E. Curry, and W. Wahlster (Eds.), *New Horizons for a Data-Driven Economy* (pp. 3–11). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-21569-3_1
Chourabi, H., Mellouli, S., and Bouslama, F., 2009. Modeling e-government business processes: New approaches to transparent and efficient performance. *Information Polity*, *14*(1, 2), 91–109.
Cohen, J., 1988. *Statistical power analysis for the behavioral sciences* (2nd ed). Hillsdale, N.J: L. Erlbaum Associates.
Daft, R. L., and Macintosh, N. B., 1981. A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units. *Administrative Science Quarterly*, *26*(2), 207–224. https://doi.org/10.2307/2392469
DeLone, W. H., and McLean, E. R., 1992. Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, *3*(1), 60–95. https://doi.org/10.1287/isre.3.1.60
DeLone, W. H., and McLean, E. R., 2003. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30.
Fernandes, R. P., Alencar, A. J., Schmitz, E. A., and Correa, A. L., 2014. Analysing IT Investments in the Public Sector: A Project Portfolio Approach. *Journal of Software*, *9*(7). https://doi.org/10.4304/jsw.9.7.1687-1700
Finansministeriet, 2017. *Regeringens kasseeftersyn på it-området*. København: Finansministeriet.
Fornell, C., and Larcker, D. F., 1981. Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 382–388.
Freund, L., Clarke, C. L. A., and Toms, E. G., 2006. Towards genre classification for IR in the workplace (p. 30). ACM Press. https://doi.org/10.1145/1164820.1164829
Gaardboe, R., Sandalgaard, N., and Nyvang, T., 2017. An assessment of business intelligence in public hospitals. *IJISPM - International Journal of Information Systems and Project Management*, (3), 5–18. https://doi.org/10.12821/ijispm050401
Gaardboe, R., and Svarre, T., 2017. Critical Success factors for Business Intelligence Success (pp. 472–486). Presented at the Proceedings of the 25th European Conference on Information Systems. The Association for Information Systems (AIS).
Gelderman, M., 2002. Task difficulty, task variability and satisfaction with management support systems. *Information & Management*, *39*(7), 593–604.
Goodhue, D., 1988. I/S attitudes: toward theoretical and definitional clarity. *ACM SIGMIS Database*, *19*(3–4), 6–15.
Hair, J., Hult, T., Ringle, C., and Sarstedt, M., 2017. *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks, CA: SAGE Publications, Inc.
Hawking, P., and Sellitto, C., 2010. Business Intelligence (BI) critical success factors. In *21st Australian Conference on Informafion Systems* (pp. 1–10). Brisbane.
Hsieh, J., Rai, A., Petter, S., and Zhang, T., 2012. Impact of User Satisfaction with Mandated CRM Use on Employee Service Quality. *MIS Quarterly*, *36*(4), 1065.
Iivari, J., 2005. An empirical test of the DeLone-McLean model of information system success. *ACM SIGMIS Database*, *36*(2), pp. 8–27. https://doi.org/10.1145/1066149.1066152
Jarupathirun, S., and Zahedi, F. "Mariam.", 2007. Dialectic decision support systems: System design and empirical evaluation. *Decision Support Systems*, *43*(4), pp.1553–1570. https://doi.org/10.1016/j.dss.2006.03.002
Khojasteh, N., Ansari, R., and Abadi, H. R. D., 2013. A Study of the Influencing Technological and Technical Factors Successful Implementation of Business Intelligence System in Internet Service Providers Companies. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, *3*(2), pp.125–132.
Kim, D. T., Kim, B. G., Aiken, M. W., and Park, S. C., 2006. The influence of individual, task organizational support, and subject norm factors on the adoption of Groupware. *Academy of Information and Management Sciences Journal*, *9*(2), pp.93–110.
Kommunernes Landsforening, 2017. Municipal Responsibilities. Retrieved May 15, 2017, from http://www.kl.dk/English/Municipal-Responsibilities/
Lee, Y. W., Strong, D. M., Kahn, B. K., and Wang, R. Y., 2002. AIMQ: a methodology for information quality assessment. *Information and Management*, *40*(2), pp.133–146.
Lewis, J. R., 1995. IBM Computer Usability Satisfaction Questionnaires: Psychometric Evaluation and Instructions for Use. *International Journal of Human-Computer Interaction.*, *7*(1), pp.57–78.
Lim, E. T. K., Pan, S. L., and Tan, C. W., 2005. Managing user acceptance towards enterprise resource planning (ERP) systems – understanding the dissonance between user expectations and managerial policies. *European Journal of Information Systems*, *14*(2), pp.135–149. https://doi.org/10.1057/palgrave.ejis.3000531
McGill, T. J., Hobbs, V. J., and Klobas, J. E., 2003. User developed applications and information systems success: A test of DeLone and McLean's model. *Information Resources Management Journal*, *16*(1), pp.24–45.

Morgeson, F. P., and Humphrey, S. E., 2006. The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, *91*(6), pp.1321–1339. https://doi.org/10.1037/0021-9010.91.6.1321

Nasab, S. S., Selamat, H., and Masrom, M., 2015. A delphi study of the important factors for BI System Implementation in the public sector organisations. *Jurnal Teknologi*, *77*(19), pp.113–120.

Nunnally, J. C., and Bernstein, I. H., 1994. The assessment of reliability. *Psychometric Theory*, *3*(1), pp.248–292.

Olszak, C. M., and Ziemba, E., 2012. Critical success factors for implementing business intelligence systems in small and medium enterprises on the example of upper Silesia, Poland. *Interdisciplinary Journal of Information, Knowledge, and Management*, *7*(2), pp.129–150.

Petter, S., DeLone, W., and McLean, E., 2008. Measuring information systems success: models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, *17*(3), pp.236–263. https://doi.org/10.1057/ejis.2008.15

Petter, S., DeLone, W., and McLean, E. R., 2013. Information Systems Success: The Quest for the Independent Variables. *Journal of Management Information Systems*, *29*(4), pp.7–62. https://doi.org/10.2753/MIS0742-1222290401

Ravasan, A. Z., and Savoji, S. R., 2014. An Investigation of BI Implementation Critical Success Factors in Iranian Context: *International Journal of Business Intelligence Research*, *5*(3), pp.41–57. https://doi.org/10.4018/ijbir.2014070104

Rosacker, K. M., and Olson, D. L., 2008. Public sector information system critical success factors. *Transforming Government: People, Process and Policy*, *2*(1), pp.60–70. https://doi.org/10.1108/17506160810862955

Seddon, P. B., 1997. A Respecification and Extension of the DeLone and McLean Model of IS Success. *Information Systems Research*, *8*(3), pp.240–253. https://doi.org/10.1287/isre.8.3.240

Straus, S. G., and McGrath, J. E., 1994. Does the medium matter? The interaction of task type and technology on group performance and member reactions. *Journal of Applied Psychology*, *79*(1),pp. 87–97. https://doi.org/10.1037//0021-9010.79.1.87

Svarre, T., and Lykke, M., 2013. Professional e-government seeking behavior. *Proceedings of the Association for Information Science and Technology*, *50*(1), pp.1–10.

Tona, O., Carlsson, S. A., and Eom, S., 2012. An empirical test of Delone and McLean's information system success model in a public organization. In *18th Americas Conference on Information Systems 2012, AMCIS 2012* (pp. 1374–1382).

Torres, L., Pina, V., and Royo, S,. 2005. E-government and the transformation of public administrations in EU countries: Beyond NPM or just a second wave of reforms? *Online Information Review*, *29*(5), pp.531–553.

Trkman, P., McCormack, K., de Oliveira, M. P. V., and Ladeira, M. B., 2010. The impact of business analytics on supply chain performance. *Decision Support Systems*, *49*(3), pp.318–327. https://doi.org/10.1016/j.dss.2010.03.007

Vandenbosch, B., and Ginzberg, M., 1997. M.J. Lotus Notes and collaboration: Plus ca change . . . *Journal of Management Information Systems*, *13*(3), pp.65–81.

Venkatesh, V., and Davis, F. D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), pp.186–204.

Wang, Y.-S., and Liao, Y.-W., 2008. Assessing eGovernment systems success: A validation of the DeLone and McLean model of information systems success. *Government Information Quarterly*, *25*(4), pp.717–733. https://doi.org/10.1016/j.giq.2007.06.002

Watson, H. J., and Wixom, B. H., 2007. The Current State of Business Intelligence. *Computer*, *40*(9), pp.96–99. https://doi.org/10.1109/MC.2007.331

Weill, P., and Olson, M. H., 1989. An Assessment of the Contingency Theory of Management Information Systems. *Journal of Management Information Systems*, *6*(1), pp.59–85.

Wixom, B., and Watson, H., 2010. The BI-Based Organization: *International Journal of Business Intelligence Research*, *1*(1), pp.13–28. https://doi.org/10.4018/jbir.2010071702

Yoon, Y., Guimaraes, T., and O'Neal, Q., 1995. Exploring the factors associated with expert systems success. *MIS Quarterly*, pp.83–106.

Appendix

Construct	Name in PLS	Question	Reference
Use	Use01	What is the approximate share of your total work tasks that were solved using [BI] in the past month?	(DeLone and McLean, 1992)
User satisfaction	UseSat01	BI has all of the functions and capabilities I expect it to have.	(Wang and Liao, 2008)
	UseSat02	If a colleague asked, then I would recommend BI.	(Batenburg and Van den Broek, 2008)
	UseSat03	Overall, how satisfied are you with BI?	(Wang and Liao, 2008)
Individual impact	IndImp01	I can effectively make my reports using BI.	(Lewis, 1995)
	IndImp02	I can complete my reports quickly using BI.	(Lewis, 1995)
	IndImp03	I can complete my reports using BI.	(Lewis, 1995)
Task compatibility	TaskCom01	This information is useful for my tasks.	(Lee, Strong, Kahn, and Wang, 2002)
	TaskCom02	This information is complete for my needs.	(Lee et al., 2002)
	TaskCom03	This information is relevant to my tasks.	(Lee et al., 2002)
	TaskCom04	This information is sufficiently up to date for my tasks.	(Lee et al., 2002)
Task difficulty	TaskDif01	BI makes it possible to complete complicated tasks.	(Morgeson and Humphrey, 2006)
	TaskDif02	The tasks I complete in BI require specialized knowledge.	(Morgeson and Humphrey, 2006)
	TaskDif03	The tasks I solve in BI, I have never met before	(Morgeson and Humphrey, 2006)
Task Interdependence	TaskInt01	If I do not complete my tasks in BI, one or more employees in the organisation cannot complete their tasks.	(Morgeson and Humphrey, 2006)
	TaskInt02	In BI, I can only do tasks if one or more employees have completed another task first.	(Morgeson and Humphrey, 2006)
	TaskInt03	I am independent of other employees to prepare tasks in BI.	(Morgeson and Humphrey, 2006)
Task significance	TaskSig01	The tasks I complete in BI are an important part of my tasks.	(Morgeson and Humphrey, 2006)
	TaskSig02	I make decisions on the basis of the tasks I complete in BI.	(Morgeson and Humphrey, 2006)
	TaskSig03	My tasks completed in BI are important to other employees in the organisation.	(Morgeson and Humphrey, 2006)
	TaskSig04	Other people make decisions based on the tasks I completed in BI.	(Morgeson and Humphrey, 2006)
	TaskSig05	My tasks in BI are important for collaborators outside the organisation.	(Morgeson and Humphrey, 2006)
Task specificity	TaskSpe01	My tasks are always defined before I complete them in BI.	(Morgeson and Humphrey, 2006)
	TaskSpe02	The tasks I complete in BI can be done in more than one way.	(Daft and Macintosh, 1981)
	TaskSpe03	Normally, I do not complete the same kinds of tasks in BI.	(Morgeson and Humphrey, 2006)